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Analysis And Interpretation of EEG Signals for BCI Applications

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Abstract -A Brain Computer Interface (BCI) allows people with severe neurological disorders to communicate with their external environment by establishing a channel between the electroencephalogram(EEG) and the computer which can be used to control a device. The classification of electroencephalogram (EEG) signals plays an important role in brain machine interface systems. Aiming to achieve pre-eminent classification of EEG types with high accuracy, a classification methodology is proposed. In the proposed methodology, EEG waveforms of classes 0, 1 and 2 are fragmented into sub signals, and experimental samples were achieved for each type of EEG signal by training and testing the dataset using different machine learning algorithms, implemented on a publicly available dataset comprising of 4 subjects,14 device channels and the 4-wave classification. The tabular results indicates the accuracy of different classification of EEG signal dataset using machine learning classifiers/algorithms.

Keywords – Brain Computer Interface (BCI), Electroencephalogram (EEG), classification

I. INTRODUCTION

The main objective of a brain computer interface (also know as brain machine interface) system is to find classifier giving more accuracy for controlling an external device using the neural activity of the brain. These Brain Computer Interface signals can be used to operated in various applications, such as controlling the movement of wheelchair or neuroprocessing for physically handicapped/individuals, traverse in a virtual environment, and supporting healthy human being in performing highly important and demanding tasks or controlling devices such as drones and some automobiles. Here we have chosen Electroencephalography (EEG) to capture brain signals or brain waves for Brain Computer Interface applications because of its simple, cheap and high accurate. The classification stage/level in BCI system is very important step in that its rate indicates one of the advantages step for Brain Computer Interface performance. In this literature, we have used some of the machine learning algorithms that are regularly used by researchers for finding accuracy.

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II. Proposed Algorithm

Classification is the process of recognizing, understanding and assembling objects into preset categories or "sub-populations" using pre organized training datasets, machine learning algorithms to classify future datasets into those categories. Classification algorithms in machine learning use input training data to forecast that the successive data will fall into one of the predetermined categories. The goal of classification is to accurately predict the labels for each category in the data and map the statistical features which are input to the corresponding category.

In this section, an EEG classification method based on Logistic Regression, KNN and SVM is discussed. The features of the EEG signal are obtained through the KNN, and then the superfluous dictionary with logistic regression is constructed based on these features.

A. K-Nearest Neighbor (KNN) Algorithm for Machine Learning

K-Nearest Neighbor is one best and efficient manageable Supervised Machine Learning classifier algorithms technique. K-NN algorithm works on the basic principle that it presume the similarity between the new point or samples and available points of all the classes and considers the new sample or data point in to the class or category that is most identical to the ready for use and accessible categories or classes. K-NN classifier or algorithm accumulates all the convenient data samples and allocates a new data sample by analyzing the resembling between the new data samples or samples and available points of the class. By this study we can say that it is easy to classify into a best suitable category based on the similarities by using K-NN classifier algorithm.

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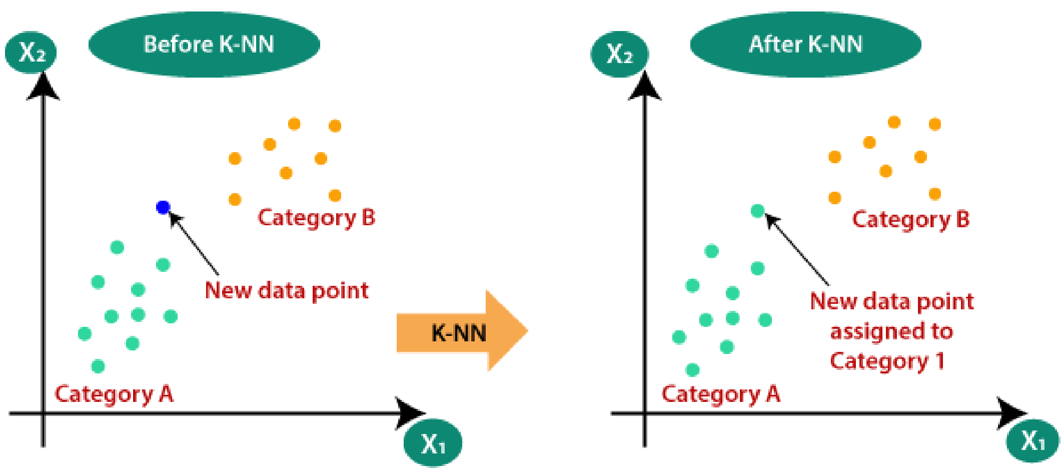

Figure 1: K-Nearest Neighbor (KNN)

Steps in K-Nearest Neighbor: *K number of neighbor points*

Step-1: Initial step is to select or assume the value for K that is the nearest neighbors.
Step-2: After choosing value for k then, by using a Euclidean distance formula determine the Pythagorean distance or Euclidean distance of K number of neighbor points.
The Pythagorean distance is defined as the range between two different extreme points on a plan geometry which may be 1-Dimentional or multi-dimensional, which we have already came across when we have studied some of the papers related to geometry. which can be calculated by substituting the values in the formula:

$$\sqrt{(X_2-X_1)^2+(Y_2-Y_1)^2}$$

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Step-3: Then by considering the K nearest neighbor points which was calculated by using Euclidean distance formula.

Step-4: Between these k neighbor points, sum up the total number of the samples or points in individual class or individual category.

Step-5: After the completion of all the above steps assign the new point or sample to the class to which number of the neighbor point is more or maximum.

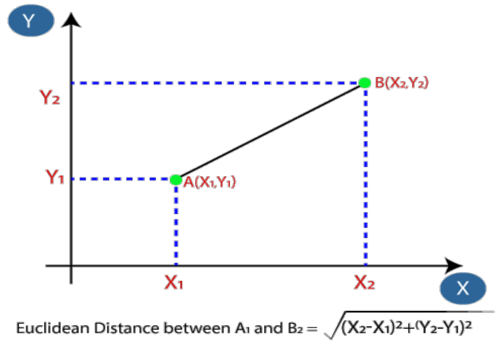
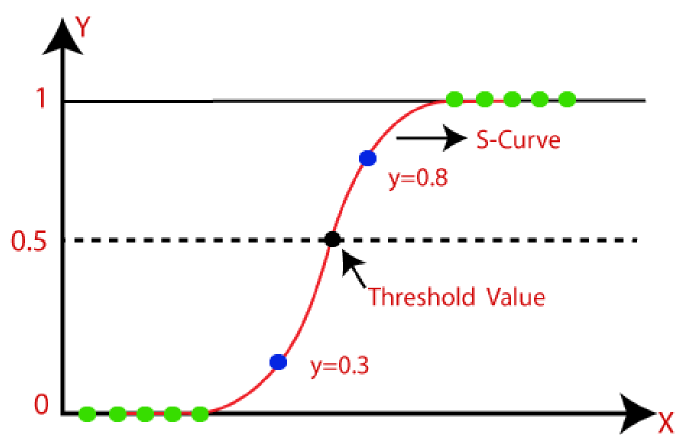


Figure 2: Calculating and Plotting Euclidean Distance

B. Logistic Regression for Machine Learning

Logistic regression projects every outcome of an absolute dependent variable. Therefore, every outcome must be an explicit or distinct variable. It can be one of two outcomes Yes or No, 0 or 1, true or False, etc., **it gives alternatively the chance values which lie between 0 and 1 than an exact value of 0 or 1**. Logistic regression, in place of suitable a regression line, we fit an "S" shaped logistic function, which predicts the greatest of two values (0 or 1).

Logistic Regression can be used to categorize the observations using various types of data and can identify the most efficient variables used for the classification. The below image is shows the logistic function:



$$\log\left[\frac{y}{1-y}\right] = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + \cdots + b_nx_n$$

Figure 3: Logistic Regression

The above equation implies the Logistic Regression.

Steps in Logistic Regression:

Step 1: The given data is preprocessed

Step 2: Logistic Regression of various values is fit to the training set

Step3: The test result is forecasted

Step 4: Test accuracy of the result is done by creating a Confusion matrix

Step 5: Envisioning the result of test set.

C. Support Vector Machine Algorithm for Machine Learning

SVM algorithm creates the best line or decision boundary that can isolate n-dimensional space into classes so that the new data point is put in the correct category in the future. This best decision boundary is termed as a hyperplane.

SVM opts for the extreme cases that help in developing the hyperplane. These extreme cases are called as support vectors, and hence algorithm is called as Support Vector Machine. The below figure shows, two different categories in which the points are classified using a decision boundary or hyperplane:

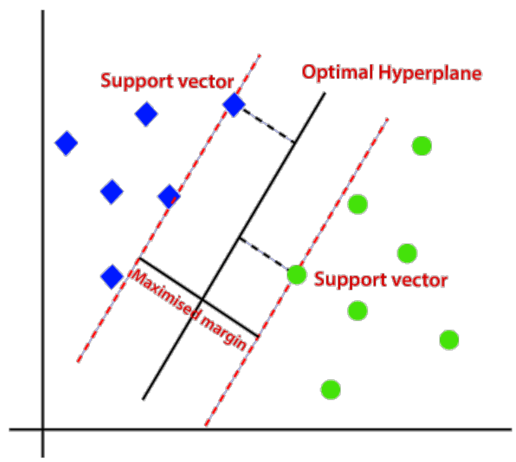


Figure 4: Support Vector Machine

Steps in SVM:

Step 1: The obtained data is preprocessed.
Step 2: SVM classifier is fit to the training set
Step 3: Forecasting the test result
Step 4: Developing the Confusion matrix and testing for the accuracy of the result.
Step 5: Implementing test result.

III. EXPERIMENT AND RESULT

The categorization of electroencephalogram (EEG) signals is important in brain– computer interface (BCI) systems which focus on achieving intelligent classification of EEG types with more precision.

BCI system functions in 4 stages:

Step 1: Signal Acquisition
Step 2: Signal Preprocessing
Step3: Decoding/Encoding
Step 4: Control and Feedback

Signal Acquisition:

For the capture of brain impulses, an EMOTIV EPOC + 14 Channel electroencephalogram from EMOTIV was used. This equipment has 128 Hz sampling frequency with 16-bit analog analog converter with 14 electrode channels: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4.

As the purpose of controlling the virtual object, a twenty-five-minute data collection protocol was created with different cycles that address different situations while the user tries to control the object. Different situations have been proposed as part of the protocol so that the machine learning component can generalize brainwave behavior withrespect to object control commands regardless of the situation.

At the period of each acquisition cycles, the participant was exposed to the images depicting voluntary motor actions,to be specific: a right arrow that would depict motor action in the right direction, a left arrow that would depict motor action from the left direction and a circle that would depict no motor action.

The only exception is the situation in which the participant is with his eyes closed, where a beep is given to the participant to open the eye only at specific times to view the images.

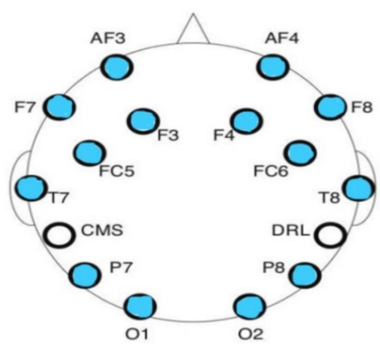


Figure 5: Electrode placement based on the international standard EEG placement system

Signal Preprocessing:

The data collected in the different situations mentioned above need to be pre-processed for later use in the machine learning component. For to better understand pre-processing, both the data source and the format and characteristics are discussed below.

The 128-Hz, 14-channel EEG equipment provides a 16-bit 128x14 matrix at each reading. As the brainwaves

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of interest are in the range of 0 to 30 Hz (Table 1), this information collected is passed by the Fast Fourier Transform (FFT) algorithm in the frequency range 0 to 30 Hz. resulting in a 30x14 matrix in the frequency domain.

After the transformation of the data collected for the frequency domain, the weighted and arithmetic mean of each wave was performed, so that the resulting matrix has the dimensions 14x4x2. Thus, each instant of data collected is represented by the weighted and arithmetic mean for each of the 14 device channels and the 4 wave classifications.

Decoding/Encoding:

Preprocessed signals are examined with modern machine learning methods to recognize brain patterns of the specified imaginations.

Control and Feedback:

Every action should cause a requisite response. If you hold a glass, you can sense the glass beyond your fingers, get a measure of its weight and sense the temperature of it. This "feedback" helps us carry out our tasks of daily life without completely acknowledging them - like modifying the hold force we put on the glass when we "observe" that it is denser than expected. For a person with no reaction in the hand, these reactions cannot be felt anymore. As a result, substitutes have to be implemented - which are called feedback.

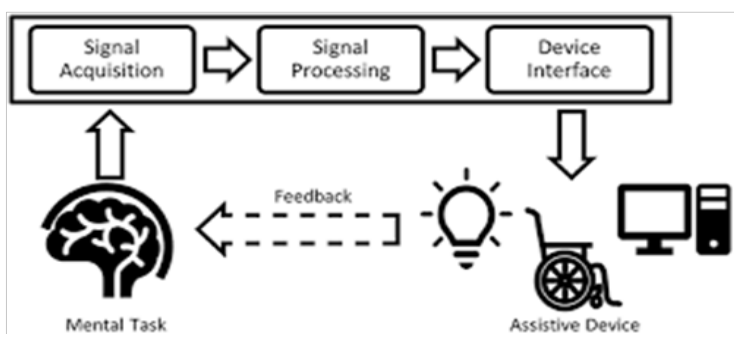

Figure 5: Methodology of Brain Computer Interface

Results:

Four subjects data was acquired and classifications of the EEG was done. The below tabular column indicates the accuracy of classification of EEG signal using machine learning classifiers.

Subject a:

Classifier	Accuracy(%)
K NEAREST NEIGHBORS	82.2917
SUPPORT VECTOR MACHINES	59.6354
LOGISTIC REGRESSION	59.2014

Subject b:

Classifier	Accuracy(%)
K NEAREST NEIGHBORS	87.5
SUPPORT VECTOR MACHINES	65.1042
LOGISTIC REGRESSION	63.8021

Subject c:

Classifier	Accuracy(%)
K NEAREST NEIGHBORS	67.4479
SUPPORT VECTOR MACHINES	50.434
LOGISTIC REGRESSION	50.2604

Subject d:

Classifier	Accuracy(%)
K NEAREST NEIGHBORS	83.1597
SUPPORT VECTOR MACHINES	55.7292
LOGISTIC REGRESSION	55.816

IV.CONCLUSION

The main aim of this article is to signify the use of suitable ML techniques for classifying EEG signals. KNN technique outcompetes the other algorithms and seems to be assuring while holding higher ordered data enabling an efficient detection of the movement as categories 0,1 and 2.

0 -- indicating neutral
1 – Right movement
2 – Left movement

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